Perceptual Grouping of Crack Patterns using Proximity and Characteristic Rules

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ABSTRACT

In this paper, we present a 2-stage approach to connected curve grouping. The algorithm is experimented and demonstrated on crack-detected images of paintings. Some features are left undetected and this tends to produce disconnected curves. In order to extract high-level features for content-based application, these supposedly connected curves have to be grouped together. It is one of the many steps needed to produce a content-based platform for digital analysis of crack patterns in paintings particularly for classification purpose. The prime objective of the grouping algorithm is to segment or partition areas of an image to produce reliable representations of *content*. The first stage of the algorithm utilizes the *Minimum Bounding Rectangle* (MBR) of a crack network as means of finding overlapping features. We demonstrate the use of the both the rotated and the un-rotated MBR. In the second stage, curve characteristics represented by the rotated MBR such as the *dimension ratio*, the *axis of minimum inertia*, *object centroid* and *node density* are used as features for an N-dimensional clustering.

KEY WORDS

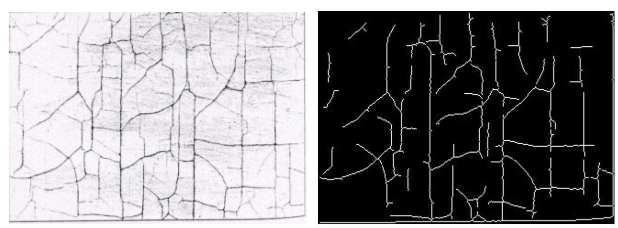
Pattern Analysis and Recognition, Machine Vision, Crack analysis, Clustering

1 Introduction

Image processing techniques have now been implemented for analysis, preservation and restoration of artwork. We have been witnessing significant growth in the number of research done on image processing related to arts ranging from quality evaluation of art images, image processing tool for art analysis, virtual enhancement as well as restoration, image retrieval and as an aid for conservation.

Craquelure in paintings is a very important element in judging authenticity, use of material or environmental and physical impact because these can lead to different craquelure patterns [3]. Although most conservation of fine artwork relies on manual inspection of deterioration signs, the ability to screen the whole collection semi-automatically is believed to be a useful contribution to preservation. Crack formations are influenced by factors including aging and physical impacts which also relate to the wooden framework of the paintings. It is hoped that the mass screening of craquelure patterns will help to establish a better platform for conservators to identify the cause of damage.

In [1] and [2] we present steps taken to implement a content-based analysis of crack pattern in paintings. Cracks are first detected using a morphological top-hat operator and grid-based automatic thresholding. From a 1-pixel wide representation of crack pattern, we generate a statistical structure of global and local features from a chain-code based representation. A well structured model of the crack patterns allows post-processing to be performed such as pruning and high-level feature extraction. At this point each crack network represents a single *content* as far as content-based analysis is concern. We call this representation a *sub-content*. Figure 1 shows sample of an image containing cracks and its crack-detected version.



(a) original image (b) crack-detected image

Figure 1. Example of crack-detected image

Questions exist at this point whether the *sub-content* is sufficient to describe a meaningful pattern. By perceptual means, it is not sufficient as the name suggests. The reasons for this are two-fold. Firstly, the crack detection process is an inherently unreliable process which results in segmentation errors such as line fragmentation. Secondly, crack patterns should be thought as combination of connected curves rather than just single connected curves. Furthermore, the regions covered by a sub-content is too small to offer meaningful features for the purposes of crack classification, information query and result representation.

Kelly et al [7] performed grouping of straight line-segments which are his objects of interest using eigenclustering. In our work, the object of interest may range from a straight line, a curve, combination of connected straight lines, combination of curves and up to the worst possible case which is a mixture of straight lines and curves.

The *Minimum Bounding Rectangle* (MBR) or in some literature known as the *Minimum Enclosing Rectangle* has been used extensively for various applications such as Computer Graphics [10] and Spatial Database Systems [5, 11]. In our work we consider 2 rectangle-shaped approximation which are the *Minimum Bounding Rectangle* (MBR) and the *Rotated Minimum Bounding Rectangle* (RMBR). The scope of our work considers having variable number of *sub-content* in a single image. Perceptually, these *sub-content* might possibly be fragments of a bigger entity of which we call a *content* or an *object*. On the other hand, they can also be a *content* or an *object* independently. The main aim of this paper is to investigate the use of these *conservative approximations* [6] not only as means of *crack network* approximation, but also to provide reliable features for pattern description.

In this paper, we show how crack patterns are grouped using a 2-stage process. The first stage uses the MBR or the RMBR as means of finding *sub-content* overlap and the second stage utilizes the features related to the RMBR as meaningful features used for clustering. Theoretical and experimental analysis are provided to show the effectiveness of the algorithm.

2 Conservative Shape Approximation

If reliable image segmentation is available, a popular approach to object classification is based on analyzing the boundaries of the extracted regions which offers 2 main benefits. Firstly, it allows simple and efficient computation of descriptors while secondly it offers a wide choice of techniques for classification based on a vector of properties [6].

Another approach for shape representation is to define a set of standard shapes such as rectangles, circles or ellipses against which input regions are compared. These representations are known as *conservative approximations* [5]. An approximation is considered conservative if an only if each point inside the contour of the original object is also in the *conservative approximations*. Several known conservative representations are the *minimum bounding rectangle* (MBR), the *rotated minimum bounding rectangle* (RMBR), the *convex hull* (CH), the *minimum bounding m-corner* (MBMC), the *minimum bounding circle* (MBC) and the *minimum bounding ellipse* (MBE) [5, 4]. These approximations differ in terms of their accuracy, area they cover and number of required parameters. Table 1 compares them in terms of the number of required parameters.

This approach allows a more general characterization of descriptors since detail information about a shape has been translated into a more simplified representation. Despite reduction in shape information, it serves well in high-volume applications where the spatial objects show a very complex structure. Computation of spatial operators is very time-intensive, therefore a simplified shape representation will allow faster computation.

conservative approx.	MBR	RMBR	CH
no. of parameters	4	5	var
conservative approx.	MBMC	MBC	MBE
no. of parameters	$2m$	3	5

Table 1. Number of parameters for conservative approximation.

* Explain the nature of the images used...several objects in an image...yStart, xStart, yDim, xDim...show mathematically.

2.1 Minimum Bounding Rectangle (MBR)

Computation of the MBR is simple and straightforward. We begin by enclosing an object which is in our scope of work named a *crack network* in a rectangle with sides parallel to the x and y axes of a cartesian coordinate system. The crack network is represented in chain form, $C = c_0c_1c_2...c_n$ where c_j are octal-valued chain links computed over $j = 0, 1..., n$. Parameters for the MBR are computed as,

$$h_{min} = \min_j \sum_{i=0}^{j} a_{iy}, \qquad h_{max} = \max_j \sum_{i=0}^{j} a_{iy}, \tag{1}$$

$$w_{min} = \min_j \sum_{i=0}^{j} a_{ix}, \qquad w_{max} = \max_j \sum_{i=0}^{j} a_{ix}, \tag{2}$$

where a_{ix} and a_{iy} are the x and y components of the vector denoted by a_i. a_{0y} and a_{0x} are both 0. h_{min} and w_{max} are the minimum and maximum pixel coordinates of the object along the y-axis while w_{min} and w_{max} are the minimum and maximum pixel coordinates of the object along the x-axis. The MBR is constructed by lines $y = h_{min}$, $y = h_{max}$, $x = w_{min}$ and $x = w_{max}$.

2.2 Rotated Minimum Bounding Rectangle (RMBR)

The computation of RMBR benefits from the concept of moments [8]. A moment of order $(p + q)$ is dependent on scaling, translation and rotation and in a digital image f, it is given as

$$m_{pq} = \sum_{i=h_{min}}^{h_{max}} \sum_{j=w_{min}}^{w_{max}} i^p j^q f(i,j) \tag{3}$$

where i and j are pixel coordinates. Since we are working with binary images, $f \in 0{,}1$. The first step involves computing the centre of mass or centroid of a crack network denoted by $(\bar{y}, \bar{x})$ and calculated as

$$\bar{y} = \frac{m_{01}}{m_{00}}, \qquad \bar{x} = \frac{m_{10}}{m_{00}}. \tag{4}$$

Translation invariance is achieved with central moments,

$$\mu_{pq} = \sum_{i=h_{min}}^{h_{max}} \sum_{j=w_{min}}^{w_{max}} (i-\bar{y})^p (j-\bar{x})^q f(i,j). \tag{5}$$

A parameter which is crucially important in our work is the direction or *axis of minimum inertia* [] θ computed as

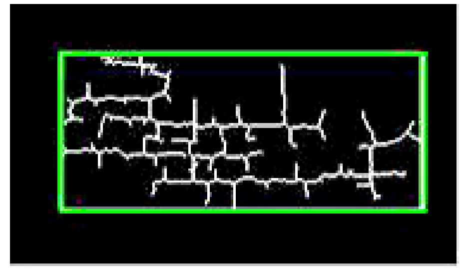
$$\theta = \frac{1}{2}\tan^{-1}\left(\frac{2\mu_{11}}{\mu_{20}-\mu_{02}}\right). \tag{6}$$

The axis of minimum inertia θ is a property which makes more sense for elongated objects, however towards computing the RMBR it is a prerequisite. The sides of the RMBR, h_R and w_R can be calculated as

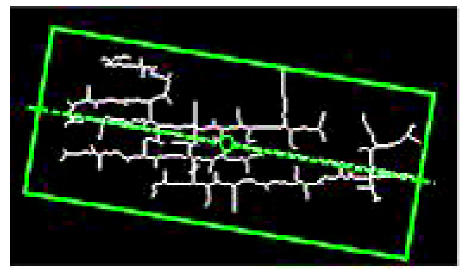
$$\begin{aligned} h_R &= \max\{y(l)\sin\theta + x(l)\cos\theta\} \\ &\quad - \min\{y(l)\sin\theta + x(l)\cos\theta\}, \end{aligned} \tag{7}$$

$$\begin{aligned} w_R &= \max\{y(l)\cos\theta - x(l)\sin\theta\} \\ &\quad - \min\{y(l)\cos\theta - x(l)\sin\theta\}. \end{aligned} \tag{8}$$

Let L be the number of non-zero pixel in the crack network, $y(l)$ and $x(l)$ are coordinates of x and y for $0 \leq l \leq L$. Figure 2 shows example of a crack network bounded by its MBR and RMBR.



(a) MBR



(b) RMBR

Figure 2. Conservative approximation of a crack network

3 First Stage of Grouping Algorithm

Once the shape approximations have been computed, a measure of homogeneity has to be established in order to group objects together.

In doing this, several criterium or characteristics can be taken into consideration. Prior knowledge as to how crack network should be grouped does in a way contribute towards deciding which criterium to employ. For instance, at this stage, we can not assume that RMBRs with similar orientation should be grouped together and at the same time we can not rule out the possibility that they should not be. It depends on how we expect the end result to be like. If we expect the end result to be a unidirectional crack, it is highly desirable to group them. On the other hand, it is less desirable if we expect a different pattern. This dilemma makes pattern characteristic less effective as a grouping rule at this stage of the process.

A criteria based on proximity and object location is expected to produce visually better results compared to a characteristic criteria. By refering to Figure 3(a), B is more likely to be grouped with A compared to C although B and C are closer in resemblance. From observation, it is more appropriate at this point to assume for merging that 2 RMBRs be evaluated in terms of their distance rather than their appearance.

3.1 RMBR Merging

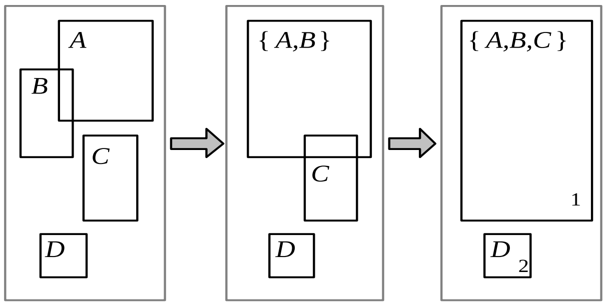
We present two merging approaches which benefits from a structured representation of *crack network*.

Let $CN1$=[$\lambda_1, \lambda_2, ..., \lambda_n$] be a list of crack network λ_i where n is the total number of network in the list. We present two approaches for RMBR merging.

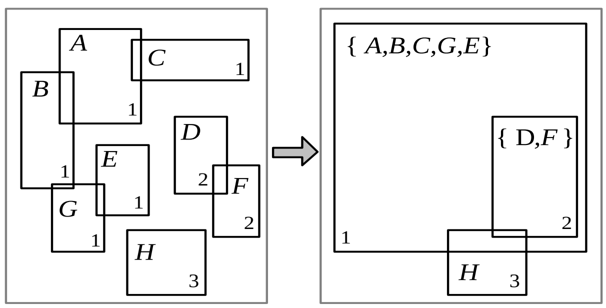
The first algorithm which we call *Merge and Expand* (M&E) is an iterative technique. For i=$1, 2, ...n$-1, λ_i is compared with λ_{i+1}. If a merge rule is satisfied, statistical values associated with λ_1 and λ_2 are combined and a new RMBR is computed. At this instance the total number of network becomes n-1, $CN1$=[$\lambda_1, \lambda_3, ..., \lambda_{n-1}$] and i=$1, 3, ..., n$-1. If λ_1 and λ_2 does not satisfy the merge rule, λ_1 is compared with λ_3 and so on until i=n-1. The process iteration is performed until no remaining RMBR pair satisfy the merge rule.

The second approach is different from the M&E in the sense that it labels every 'connected' RMBR at a first run and merge their properties later at a second run. We name this approach the *Label and Merge* (L&M) technique. For i=$1, 2, ...n$-1, λ_i is compared with λ_{i+1}, λ_{i+2},...,λ_{i+n-1}. If any of the RMBR pair satisfy a merge rule, label them with the same label.

Figure 3 illustrates these two algorithms.



(a) *Merge and Expand*



(b) *Label and Merge*

Figure 3. Content merging approaches

4 Merge Rule: Overlap Test

In our scope of work, proximity can be defined several ways. To decide whether two approximations should be merged, there are several decision rules that can be considered . The first being a measure of distance between two approximations and the second being an assessment of logical operations between two approximations.

Two approximations should be merged only if the distance between them is below a threshold. Computing distance between two approximations is a straightforward task. The only tricky part of this is to decide on which two points (or more) of the approximations to be used as representative points. The simplest option is the centroid. However, in global terms, finding the right solution is not as simple because with variable number of crack network in an image, it is not as straightforward to determine the optimum distance (threshold) between approximations.

The second technique uses logical operations to decide on merging. Two approximations will only be merged if they overlap or intersect. In mathematical terms, refering to Figure **??**, we can decide to merge A and B only if A $\cap$ B $\neq \emptyset$.

Why opt for this test? Speed? Simplicity for real-time.

4.1 MBR Overlap Test

Let P_a and P_b be two sets of corner points for A and B respectively where:

- $P_a = \{h_{min_a}, w_{min_a}, h_{max_a}, w_{max_a}\}$ and
- $P_b = \{h_{min_b}, w_{min_b}, h_{max_b}, w_{max_b}\}$.

A and B is merged if one or more of the following conditions are met:

- $h_{min_b} \leq h_{min_a} \leq h_{max_b}$
- $w_{min_b} \leq w_{min_a} \leq w_{max_b}$
- $h_{min_b} \leq h_{max_a} \leq h_{max_b}$
- $w_{min_b} \leq w_{max_a} \leq w_{max_b}$
- $h_{min_a} \leq h_{min_b} \leq h_{max_a}$
- $w_{min_a} \leq w_{min_b} \leq w_{max_a}$
- $h_{min_a} \leq h_{max_b} \leq h_{max_a}$
- $w_{min_a} \leq w_{max_b} \leq w_{max_a}$

4.2 RMBR Overlap Test

Let R_a and R_b be two sets of required parameters of an RMBR where

- $R_a = \{\theta_a, \bar{y}_a, \bar{x}_a, h_a, w_a\}$,
- $R_b = \{\theta_b, \bar{y}_b, \bar{x}_b, h_b, w_b\}$,

with θ, $\bar{y}$, $\bar{x}$, h and w being the *axis of minimum inertia*, y-centroid, x-centroid, RMBR height and RMBR width respectively. Line intersections and corner points can be calculated from the five parameters using trigonometric computation. From the 10 parameters of the two RMBRs, 8 corner points and 16 possible line intersections are computed. Let C_a and C_b be two sets of corner coordinate points for A and B respectively, where

- $C_a = \{(y_{a_1}, x_{a_1}), (y_{a_2}, x_{a_2}), ..., (y_{a_4}, x_{a_4})\}$,
- $C_b = \{(y_{b_1}, x_{b_1}), (y_{b_2}, x_{b_2}), ..., (y_{b_4}, x_{b_4})\}$.

Similarly, let I be a set of all possible intersection coordinate points between A and B, where

- $I = \{(\hat{y}_1, \hat{x}_1), (\hat{y}_2, \hat{x}_2), ..., (\hat{y}_{16}, \hat{x}_{16})\}$.

Using C_a, C_b and I we can determine whether A intersects with B by underlining some logical rules.

We conduct tests on an image containing crack patterns (as shown in Figure 4) by using the algorithms described in Section 3 while employing merging rules as explained in Sections 4.1 and 4.2. The results are as shown in Figure 6.

As can be seen, Figure 6(a) produces visually good result, the closest to the expected outcome. It is important to note that although it produces the best result, it does not mean that the same technique will work similarly good on

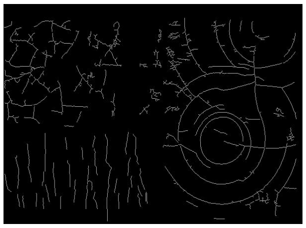
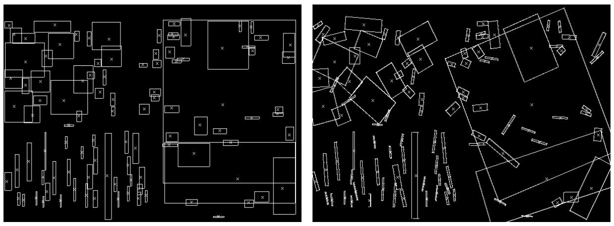


Figure 4. Crack detected image.



(a) *MBR* ⇒MBR (b) RMBR

Figure 5. *sub-content* before merging approximated by the MBR and the RMBR

other images. As can be seen from Figure **??**(a), the small RMBRs are supposed to be merged. They, if grouped will form a *unidirectional* pattern. However, since their RMBR do not intersect, they are not grouped at this point. The next section explains an approach taken to deal with this situation.

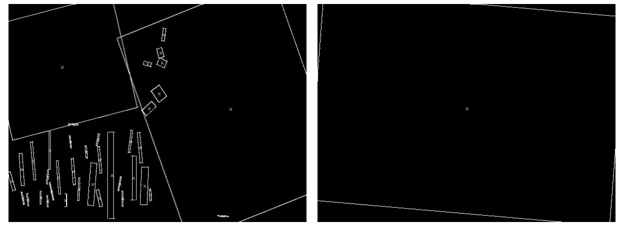
5 Second Stage of Grouping Algorithm

RMBR pairs which are in close proximity with one another have been merged. However, a second stage is still needed in order to group RMBRs which does not conform to the merging rule but still posses great level of similarity with their neighbours.

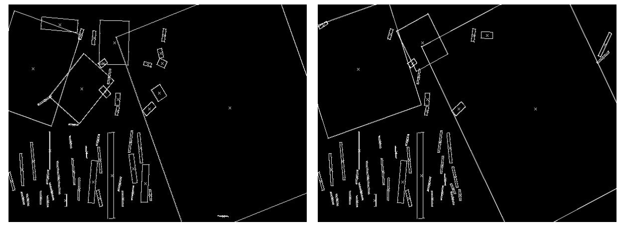
Based on early experiments, we identify several features as potentially good descriptors for further grouping. They are the absolute value of the *axis of minimum inertia* $|\theta|$, the *dimension ratio* α, the *node density* δ, the *y-centroid* $\bar{y}$ and the *x-centroid* $\bar{x}$. Assuming that in a crack network, there are x number of nodes or junctions, the node density $\delta = x/(h_R \text{ x } w_R)$ while the dimension ratio is the ratio between the height h_R and the width w_R of an RMBR expressed as $\alpha = h_R/w_R$. These features are arranged as a feature vector, $V = (\ \bar{y},\ \bar{x},\ |\theta|,\ \alpha,\ \delta\ ) = (v_1, v_2, v_3, v_4, v_5)$.

5.1 Feature Clustering

Experimentally, every image tested have variable number of RMBRs. The number of feature vectors associated with



(a) *M&E* ⇒MBR (b) *M&E* ⇒ RMBR



(c) *L&M* ⇒MBR (d) *L&M* ⇒RMBR

Figure 6. Results of merging using M&E, L&M approaches with MBR, RMBR merging rules.

each image depends on the number of RMBR. To demonstrate the effectiveness of the features, we perform a 5-dimensional hierarchical clustering using a variable number of feature vector V. The features are first normalized over all RMBR to produce a mean of zero and standard deviation of zero for each feature element.

Using the *euclidean distance* as a distance measure we perform hierarchical clustering on the feature points using the *complete-link* algorithm [12, 13].

A dendrogram corresponding to the hierarchically clustered feature points for the image in Figure 6(a) is as graphically shown in Figure 7.

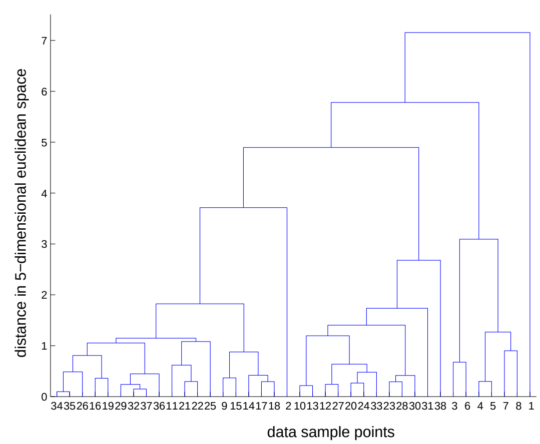
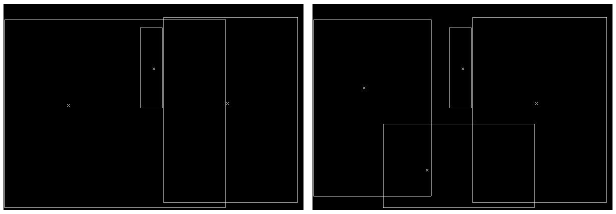


Figure 7. The dendrogram of the clustered data.

We then manually select the number of expected objects in the image which is 3 or 4 which then yield the following result as illustrated by Figure 8.



(a) 3-class (b) 4-class

Figure 8. Results after 2nd stage of *sub-content* grouping

6 Conclusions and Future Work

Perceptual grouping of *crack network* using a 2-stage approach has been outlined and explained. We have discussed the use of *conservative approximation* in grouping *crack network* in the form of connected curves. We experimented techniques of content merging (i.e the *Merge and Expand* (M&E) and the *Label and Merge* (L&M)) using the overlapping between pairs of either the *Minimum Bounding Rectangle* (MBR) or the *Rotated Minimum Bounding Rectangle* (RMBR) as a triggering factor for merging. We also performed clustering on selected features derived from the RMBR.

Line/curve grouping and classification is an area of research which takes quite a lot of attention from researchers. Having said that, looking from a wider scope, with ramifications and improvements our approach can be of benefit not only to this particular area, but also to fields such as data indexing and query/result processing in content-based retrieval systems.

As for the future, we are looking into improving the algorithm by embedding adaptive functionalities in certain parts. Weighted distances can be used in determining the distance between feature points in the second stage of the algorithm. Weights can be assigned to an object based on a characteristic they possess such as their size which in this case the weighting can be proportional to the size. An adaptive way of knowing the optimum number of objects or *content* in a particular image is also a big challenge at this point. There are quite a number of adaptive clustering techniques with variety of advantages and weaknesses.

We are also still investigating the use of 'fine' *crack network* features aside from the ones discussed in [1] and [2]. In this paper we experimented using 'coarse' features which are derived from the *conservative approximation*, i.e RMBR of a *crack network*. It is believed, a more detail description of the object of interest might result in a better outcome.

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